GUIDED FILTER BASED IMAGE FUSION ALGO - RITHM IN LIFTING WAVELET DOMAIN

A DISSERTATION SUBMITTED IN PARTIAL FULFILL - MENT OF THE REQUIREMENTS

FOR THE AWARD

OF THE DEGREE

OF

MASTER OF TECHNOLOGY

IN

Signal Processing & Digital Design

Submitted by

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CANDIDATE'S DECLARATION

I VIPUL RANA,2K16/SPD/17 student of M.Tech (Signal Processing and Digital Design),hereby declare that the project Dissertation titled "GUIDED FILTER BASED IMAGE FUSION ALGORITHM IN LIFTING WAVELET TRANSFORM DOMAIN" which is submitted by me to the Department of ELECTRONICS AND COMMUNICATION, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology.

Place: Delhi (VIPUL RANA)

Date:

CERTIFICATE

I hereby certify that the Project Dissertation titled "**Guided filter-based image fusion algorithm in Lifting wavelet transform domain**" which is submitted by VIPUL RANA**,** 2K16/SPD/17 Electronics and Communication, Delhi Technological University, Delhi in the partial fulfillment of the requirement for the award of the degree of the Master Technology is the project work carried under my supervision.

Place:Delhi **(Dr.Sudipta Majumdar)**

Date: **SUPERVISOR**

ACKNOWLEDGEMENT

Firstly, I would like to express my sincere gratitude to my mentor and supervisor, Dr.Sudipta Majumdar Mam for her constant guidance, encouragement and support. I am thankful to the Electronics and Communication Engineering Department of Delhi Technological University for providing me with unparalleled facilities. I extend my gratitude to researchers and scholars whose papers and thesis have been utilized in my project. Finally, I dedicate my project report to my parents for their love, support and encouragement without which this would not have been possible.

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ABSTRACT

This work presents fusion of medical images using guided filter (GF) in lifting wavelet transform domain. The medical images used are CT and MRI. The lifting wavelet transform have been implemented on CT and MRI images to obtain the sub-images i.e. LL, LH, HL and HH sub-images. By comparing the LL sub-images of input images, the weight maps have been obtained. Then, the refined weight map has been obtained using the Gaussian filter. Now for obtaining the guided image the Canny edge detector is used. Finally, using the weight maps as the input image of the guided filter and the edge detected image using canny operator as the guided image, guided filter has been designed. The approximation and wavelet coefficients of CT and MRI images are fused according to the weighted fusion rule using refined weight maps. A fused image of CT and MRI has been obtained by the inverse lifting wavelet transform. The proposed method has been compared with **Choose-max method, intuitionistic fuzzy inference method** and **guided filter based wavelet transform method** for fusion. The image fusion has been evaluated using entropy, correlation, average gradient, edge strength. Simulation results present the better performance of the lifting wavelet domain based fusion method in terms of these parameters. Also the use of the lifting wavelet transform has the advantage of smaller complexity as compared to the first generation wavelets.

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1.INTRODUCTION

1.1OBJECTIVE

It is advantageous to have complementary information in a single image which are provided by different modalities of imaging system. This is particularly useful for medical images and satellite images etc. As different imaging systems use different physical phenomena/principles for imaging, they provide complementary information provided by various modalities of images into a single image that can be used for various applications. The image fusion requires registered images i.e. it rises aligned images for fusion purpose. For example MRI images provide good information about soft tissue, whereas it is not able to provide clear information of hard tissues and bones. Whereas the CT scan provides good information about hard tissues. The CT uses ionizing radiation together with an electronic detector array to record the density pattern. The MRI uses the magnetic properties of atomic nuclei. The radio waves are used to rotate the nuclei and they emit radio signal due to oscillations in the magnetic field. So various techniques have been presented in literature for image fusion.

1.2 LITTERATURE REVIEW

The integration of multi source images provides wide information for research and analysis. Fusion of images is an important research area for medical images. Hence, various methods for image fusion in medical imaging were proposed. These methods were choose-max algorithm, fuzzy inference method, Intuitionistic fuzzy inference algorithm for fusion. In choose-max algorithm[2] the fusion is done by comparison of the gray-scale values of each pixel in the input image by replacing as the gray value of the fused image by the larger gray value in the neighborhood pixel. Fuzzy inference is a technique which utilizes the technology of artificial intelligence[3] for fusion by extracting features and then make decision based on a certain rule. Guided filtering based image fusion method[1] is a new method introduced for fusion using lifting wavelet transformation along with guide filtering.

1.3 WAVELET TRANSFORM

Wavelet Transform (WT) is efficient tool for transient and non-stationary signal analysis. It is able to find the local and global analysis of a signal by varying the resolution. WT has advantage of multi resolution as compared to short time Fourier transform.

The main characteristics of WT is written as:-

$$\int_{-\infty}^{+\infty} \psi(t) = 0$$

This shows that wavelet is oscillatory in nature and the mean value is zero. The condition that the Signal can be reconstructed from the inverse wavelet transform condition is given by:-

$$\int_{-\infty}^{+\infty} \frac{|\widehat{\psi(w)}|^2}{|w|} = C_\psi < \infty$$

Where $\psi(w)$ is the Fourier transform of $\psi(t)$.

The disadvantages of DWT is it requires large memory with high computational time length, but the advantage is that it provides multi resolution analysis. Lifting wavelet transform is the second generation wavelet which does not involve the translation and scaling as used in first generation wavelet transform. It is derived in the spatial domain. Lifting wavelet transform scheme consists of following steps:-

1. Split step: The signal, X (n), is splitted into odd and even samples.

2. Lifting step: In this step, the odd and even samples are filtered by the prediction and update filters, p(z) and u(z).

3. Normalization or Scaling step: After N lifting steps, scaling coefficients K and 1/K are applied respectively to the odd and even samples in order to obtain the low pass sub band YL(i) and the high-pass sub band YH(i).

1.4GUIDED FILTER

Guided filter[2] is derived from a local linear model that generates the filtering output by considering the content of a guidance image, which can be the input image itself or another different image.

1.5 EDGE DETECTION

Various methods such as Canny edge detector, Sobel, Laplacian of Gaussian have been used in literature for edge detection.

Thesis is organized as follows:- Chapter 2 presents brief theory of guided image filter. Chapter 3 provides brief theory of wavelet transform. Chapter 4 presents various image fusion techniques used in literature. Proposed method is presented in chapter 5. Chapter 6 provides the simulation results. Finally chapter 7 concludes the work and presents the future scope.

2.GUIDED IMAGE FILTERING

Guided filter is an explicit filter which computes the output image by using the content of a guidance image. This image can be the input image or any other image. One example of guided filter is edge preserving, which can be used as smoothing operator for preserving the edges such as bilateral filter. The guided filter has many applications in image dehazing , edge smoothening, image enhancement and image upsampling. The guided image provides the output filtered image by using a reference image.

2.1 GUIDED FILTER

Using I as a guidance image and q as a guided filter the guided filter if define below. Assuming t q as a linear transformation of I in a window w_k centered at the pixel k: -

q_i = $a_k I_i$+b_k $\forall$ I ϵw_k

where (a_k, b_k) are taken as constant in w_k .We use square window of a radius r. The linear coefficients ($a_{k,} b_k$) are obtained by minimizing the cost function in window w_k .The cost function in the window w_k is given as:

$$E(a_k, b_k) = \sum_{w_k}((a_k I_i + b_k - P_i)^2 + \in a_k^2)(1)$$

where, $\in_k$ is a regularization parameter, it is the degree of blur that controls the edge detection accuracy. The output of the guided filter provides an average result of input image in window w_k in absence of edges in image I. If image I contains edges then there edges are transformed to the output image. The $a_{k,}$&b_k coefficients can be obtained by using the linear ridge regression model for the cost function given below:-

For a linear fit,

$$f(a, b) = a + b\,x, \qquad (3)$$

$$R^2(a, b) \equiv \sum_{i=1}^{n}[y_i - (a + b\,x_i)]^2$$

(4)

$$\frac{\partial(R^2)}{\partial a} = -2\sum_{i=1}^{n}[y_i - (a + b\,x_i)] = 0 \tag{5}$$

$$\frac{\partial(R^2)}{\partial b} = -2\sum_{i=1}^{n}[y_i - (a + b\,x_i)]\,x_i = 0. \tag{6}$$

So we have:

$$n\,a + b\sum_{i=1}^{n} x_i = \sum_{i=1}^{n} y_i \tag{7}$$

$$a\sum_{i=1}^{n} x_i + b\sum_{i=1}^{n} x_i^2 = \sum_{i=1}^{n} x_i\, y_i. \tag{8}$$

Or

$$\begin{bmatrix} n & \sum_{i=1}^{n} x_i \\ \sum_{i=1}^{n} x_i & \sum_{i=1}^{n} x_i^2 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} x_i\, y_i \end{bmatrix}, \tag{9}$$

so

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} n & \sum_{i=1}^{n} x_i \\ \sum_{i=1}^{n} x_i & \sum_{i=1}^{n} x_i^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} x_i\, y_i \end{bmatrix}. \tag{10}$$

The 2x2 matrix inverse is

$$\begin{bmatrix} a \\ b \end{bmatrix} = \frac{1}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \begin{bmatrix} \sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i\, y_i \\ n\sum_{i=1}^{n} x_i\, y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i \end{bmatrix}, \tag{11}$$

So

$$a = \frac{\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i\, y_i}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \tag{12}$$

$$= \frac{\bar{y}\left(\sum_{i=1}^{n} x_i^2\right) - \bar{x}\sum_{i=1}^{n} x_i\, y_i}{\sum_{i=1}^{n} x_i^2 - n\,\bar{x}^2} \tag{13}$$

$$b = \frac{n\sum_{i=1}^{n} x_i\, y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2}$$

$$b = \frac{(\sum_{i=1}^{n} x_i\, y_i) - n\,\bar{x}\,\bar{y}}{\sum_{i=1}^{n} x_i^2 - n\,\bar{x}^2} \tag{14}$$

So the final solution obtained by using the single fit- regression model are as follows:-

$$a_k = \frac{\frac{1}{|w|}\sum_{i\in w_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \in}$$

$b_k = \bar{p}_k$ - $a_k \mu_k$

Here μ_k and σ_k^2 are the mean and variance of I in w_k, |w| is the number of pixels in w_k and $\bar{p}_k = \frac{1}{|w|}\sum_{i\in w_k} p_i$ is the mean of p in w_k. Then we can compute the filtering output. A pixel i which is covered over all the overlapping windows w_k but the filtered output q_i is not when identically computed at different windows. To make the output same, average all the possible values of q_i of overlapped windows. So by computing (a_k, b_k) , the output after filtering by the linear ridge regression model using:-

$O_i = \frac{1}{|w|} (\sum_{k|i\in w_k}(a_k I_i + b_k)$(2)

As $\sum_{k|i\in w_k} a_k = \sum_{k\in w_i} a_k$ is due to the symmetry of the box window, the equation can be

rewritten as

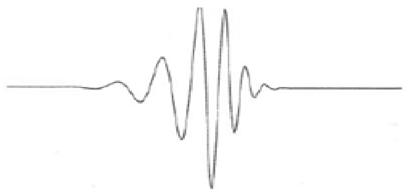
$\overline{q_i} = \bar{a}_k I_i + \overline{b_k}$(3)

where $\bar{a}_i$ and $\bar{b}_i$ are the average values over all overlapping windows at i.

3.WAVELET TRANSFORMS

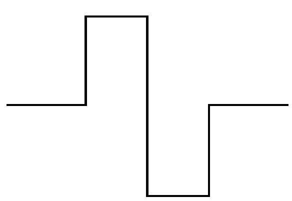
3.1 WAVELET

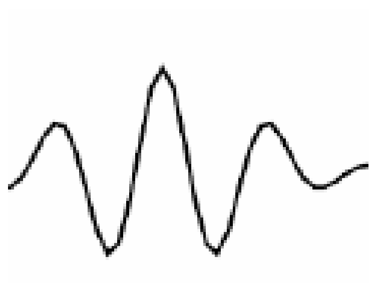
Wavelet is a small wave which is oscillatory in nature and having compact support.

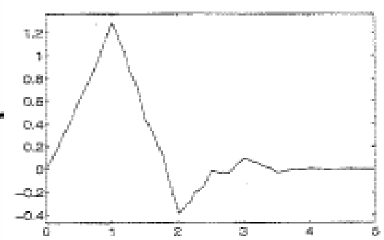


4. There are many different wavelets, for example:-

1. Haar wavelet 2. Morlet wavelet 3. Daubachies wavelet







5. The wavelet transform can be classified into two classes:-
    1. CWT
    2. DWT

3.2 CONTINUOUS WAVELET TRANSFORM

Let us define a basis function ψ(x) and assume that it is band limited with its d.c. component equal to zero. Translated and scaled version of function ψ(x) is defined as:-

$$\psi_{s,t}(x) = \frac{1}{\sqrt{s}}\,\psi\left(\frac{x-t}{s}\right)$$

where t is the translational parameter &s is the scaling parameter

Continuous wavelet transform of f(x) is defined as:

$$W_{\varphi}(s,t)=\frac{1}{s}\int_{-\infty}^{+\infty} f(x)\, \psi_{s,t}^{*}(\frac{x-t}{s})dx$$

- The admissibility condition is

$$c_{\psi}=\int_{0}^{\infty} \mid \hat{\psi}(\omega) \mid^{2} \frac{d\omega}{\mid \omega \mid} < \infty$$

- Regardless of its scale and magnitude, a function ψ is admissible as a wavelet if and only if mean is zero.

$$\int_{-\infty}^{\infty} \psi(t)dt = 0$$

3.3DISCRETE WAVELET TRANSFORM

It is same as continuous wavelet transform except that scales and translations are choosen based on the powers of 2.

$$\psi_{j,k}(x)=2^{\frac{j}{2}}\psi(2^{j}x-k)$$

The discrete function f(n) can be represented as the weighted sum of wavelet approximation and detailed coefficients as :-

$$f(n) = \frac{1}{\sqrt{M}}\sum_{k} w_{\varphi}(j_{o},k)\varphi_{j_{o},k}(n) + \frac{1}{\sqrt{M}}\sum_{j=j_{o}}^{\infty}\sum_{k} w_{\psi}(j,k)\varphi_{j,k}(n)$$

where j_o is the scale and n= 0,1,2…….M

For a signal S of length *N*, two sets of coefficients approximation coefficients *CA1*, and detail coefficients *CD1* are computed as:

Approximation coefficient $W_{\varphi}(j,k) = \frac{1}{\sqrt{M}}\sum_{x} f(x)\, \varphi_{j,k}(x)$

Detailed coefficient $W_{\psi}(j,k) = \frac{1}{\sqrt{M}}\sum_{x} f(x)\ \psi_{j,k}(x)$

The implementations of DWT on an image provides four subimages as- (1) LL, (2) LH, (3) HL and (4) HH. Here, L stands for low-pass filtering, and H stands for high-pass filtering.

TWO-DIMENSIONAL DWT

Decomposition steps

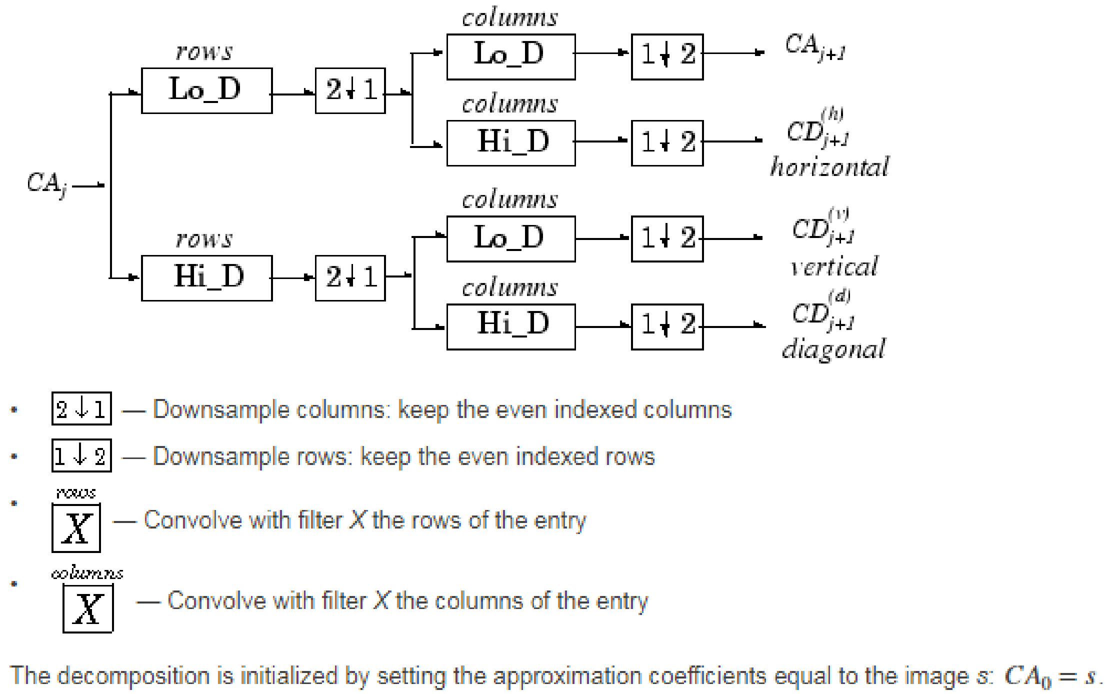


Fig.7 2D- DWT FORMULATION

Disadvantages of DWT[1]

1. Large memory requirement due to involvement of large number computations.
2. Large computational time length.
3. Cumbersome hardware implementation.
4. Due to down-sampling at every stage leads to boundary extensions. These boundary extension leads to loss of information.

3.4 <u>LIFTING WAVELET TRANSFORM</u>

The LWT is a second generation wavelet which has several advantages compared to first generation wavelets. They are:-

1. LWT requires smaller computation as compared to the first generation wavelets.
2. Due to in-place calculation LWT requires smaller memory storage.
3. Implementation of integer to integer transformation is provided by LWT.

3.4.1 BASIC LIFTING INTRODUCTION

Polynomial interpolation function which are used for wavelet transform algorithms can approximate a set of data, they are called as predict wavelets. Wavelet algorithms have one central feature that the data is represented by multiple resolutions but the predict wavelets does not hold such kind of feature. This is due to the fact that averaging step is not performed, therefore the differences stored in the predict step are larger. Hence the wavelet based algorithms such as noise reduction (or signal estimation) does not goes well, without averaging step. So the basic lifting wavelet is describing by both predict wavelet and averaging update wavelet.

The Predict Wavelets

This step divides the input signal into even indexed and odd indexed data sets. The even indexed elements are considered as the input for the next step in the transformation. Generally, odd values are predicted from the even values as shown below by the equation:-

$odd_{j+1,i} = odd_{j,i} - P(even_{j,i})$ where P is a predictor filter

In inverse predict wavelet transform the prediction value is summed to the odd element (inverse the prediction step in the forward transform) & followed by the merging step which actually interleaves the odd and even elements again into a single data stream

The update step

The even elements with an average are replaced by an update step. The approximation of the original data set represented by an odd elements that allows construction of filters.

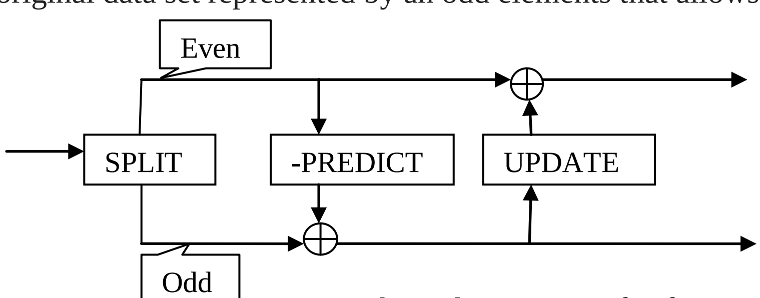


Figure9 shows basic steps of Lifting Wavelet Transform

The predict step is followed by the update step.

$\text{even}_{j+1,i} = \text{even}_{j,i} + \boldsymbol{U}(\ \text{odd}_{j+1,i}\ )$

3.2.2Lifting Scheme for the Daubechies Db4 Transform

Forward Lifting Wavelet Transform

The Forward lifting steps of the Daubechies Db4 step equations:-

$s_l^{(1)} = x_{2l} + \sqrt{3}x_{2l+1}$

$d_l^{(1)} = x_{2l+1} - \frac{\sqrt{3}}{4}s_l^{(1)} - \frac{\sqrt{3}-2}{4}s_{l-1}^{(1)}$

$s_l^{(2)} = s_l^{(1)} - d_{l+1}^{(1)}$

$s_l = \frac{\sqrt{3}-1}{\sqrt{2}}s_l^{(1)}$

$d_l = \frac{\sqrt{3}+1}{\sqrt{2}}d_l^{(2)}$

Inverse Lifting Wavelet Transform

The reverse lifting steps of the Daubechies Db4 step equations:-

$d_l^{(1)} = x_{2l+1} - \frac{1}{\sqrt{3}}x_{2l+2}$

$s_l^{(1)} = x_{2l} - \frac{(6-3\sqrt{3}\,)}{4}d_l^{(1)} - \frac{\sqrt{3}}{4}d_{l-1}^{(1)}$

$d_l^{(2)} = d_l^{(1)} - \frac{1}{3}s_1^{(1)}$

$$s_l = \frac{3+\sqrt{3}}{3\sqrt{2}} s_l^{(1)}$$

$$d_l = \frac{3-\sqrt{3}}{3\sqrt{2}} d_l^{(2)}$$

4. IMAGE FUSION

Image fusion is used to obtain the complementary information provided by different imaging techniques into a single image.

1. Signal Level Fusion :- This is the low level fusion, in which raw images are fused.
2. Pixel Level Fusion :- In this, pixel wise fusion is performed.
3. Feature Level Fusion:-In this level, features are extracted and then fused.
4. Decision Level Fusion:- This is a high level fusion in which decisions coming from various fusion algorithms are fused.

4.1VARIOUS PARAMETERS FOR PERFORMANCE EVALUATION OF OUTPUT FUSED IMAGE

Suppose for evaluation purpose let image B is the output image which we get after the fusion and the size of B is $M \times N$, where M , N are the rows ,columns of the output image, respectively and Bi, j is the pixel value at the location (i, j).

4.1.1SPATIAL PARAMETERS[3]

1.Mean$\overline{B}$:-The average value of fused image B is given by:-

$$\overline{B} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} B_{i,j}}{M \times N}$$

2.Average gradient G:- The average gradient G shows the tiny details or minute details variations in contrast of an image, which is also termed as marginalisation degree of the output obtained .The higher image clarity indicates the larger average gradient of an image. The average gradient G is shown as bellow:-

$$\overline{G} = \frac{1}{(M-1)\times(N-1)}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{\frac{S_x^2(i,j)+S_y^2(i,j)}{2}}$$

Where $Sx(i, j)$& $Sy(i, j)$ indicates the first-order partial derivative in horizontal and vertical directions at pixel(i, j)respectively using Sobel operator.

<u>3.Edge Strength</u>:-The edge strength shows the degree of clarity in image. The proposed method to calculate the edge strength is given as below: - the second-order partial derivative in four directions (horizontal, vertical, diagonal and back-diagonal) are calculated using the neighbor-hood pixel values, which are expressed as HOE(i, j), VOE(i, j), DOE(i, j) and BOE(i, j), respectively. Thereafter maximum value out of the four directions is selected as the edge strength at pixel (i, j) , and the edge strength ES of image B is obtained by averaging all of the edge strengths of each pixel :-

$$\text{ES} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} max \begin{Bmatrix} HOE(i,j), VOE(i,j) \\ , DOE(i,j), BOE(i,j) \end{Bmatrix}$$

4.1.2 INTENSITY PARAMETERS

The entries of gray level co-occurrence matrix GLCM matrix are divided by the total sum of the entries of GLCM Matrix G. This quantity

$$P_{ij} = \frac{g_{ij}}{\sum g_{ij}}$$

$\sum_{j=1}^{k} \sum_{i=1}^{k} P_{ij} = 1$ where k is the row, column of square matrix G

<u>4.Correlation</u>:-It gives a measure of how much a pixel is correlated to its neighboring pixel over the entire range [1,-1].

$$\text{Correlation} = \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{(i-m_r)(j-m_c)P_{ij}}{\sigma_r \sigma_s} \quad \text{,where} \quad \sigma_r \neq 0 \text{ , } \sigma_s \neq 0$$

Where m_r ,m_c are mean along x, y direction &σ_r , σ_s are standard deviation along x, y direction

<u>5.Entropy</u>:-Entropy gives us the measurement of degree of randomness in textural content of the image . The maximum value is $2log_2K$.

Entropy = - $\sum_{i=1}^{k} \sum_{j=1}^{k} p_{ij}\ log_2 p_{ij}$

5.CANNY EDGE DETECTOR

Simple image differencing operators for edge detection have problems like:-

1. Spurious due to noise

2. Multiple responses to a single edge

3. Therefore major difficulty is in localizing the genuine edges.

The Canny edge detector[6] provides

1. Good edge detection :– Algorithm detects real edge points and discard false edge points .
2. Good edge localization :- Algorithm's ability to produce edge points close to real edges.
3. Only one unique response to each edge:- Algorithm should not produce any false, double ,or spurious edges.

STEPS FOR CANNY EDGE DETECTOR

Step1. Convolve the image f(x,y) with the Gaussian filter

$$G(x,y) = \exp\left(\frac{-(x^2-y^2)}{2\sigma^2}\right)$$

$F_r(x,y) = G(x,y) * f(x,y)$, where* is the convolution operator

Effects:-

-smoothening of the image.

-Noise Removal.

Step2. Compute the Gradient magnitude and direction at every pixel f(x,y) using Sobel Mask.

$$M(x,y) = \sqrt{g_x^2 + g_y^2} \; \& \;\; \alpha(x,y) = \tan^{-1}\left(\frac{g_y}{g_x}\right)$$

Step3. By using the threasholding condition, we can localize edges, and the edges magnitude and orientation is stored separately two arrays.

Step4. To obtain thin edges, apply non-maxima separation.

Non-Maximum Suppression

- Discretize (i.e. quantize) the edge directions to 4 prominent sectors
  (0-360 degree) is divided into 8 equal parts and two portions are designated as 1 sector
- Therefore there will be four sectors.
- Gradient direction of the edge point is approximated to these four sectors (45, 135,225,315).
- Define a 3X3 neighborhood around every pixel.

- Along d_k,verify that pixel(x,y) in the k direction that has a maximum for M(x,y), if not then suppress it to zero.

Step 5:- Use double threasholding to retain the four edges:-

- **High Threashold :-** It gives all the strong edges but misses out the weaker edges.
- **Low Threashold :-** It gives weaker edges, but also gives spurious noise responses due to noise.

Step6:-Examine the connectivity of strong edge pixels and retain the weak edges which are connected to strong edge pixels. The weak edges points that are not connected to strong edges are considered as noise and are discarded.

6. PROPOSSED METHOD

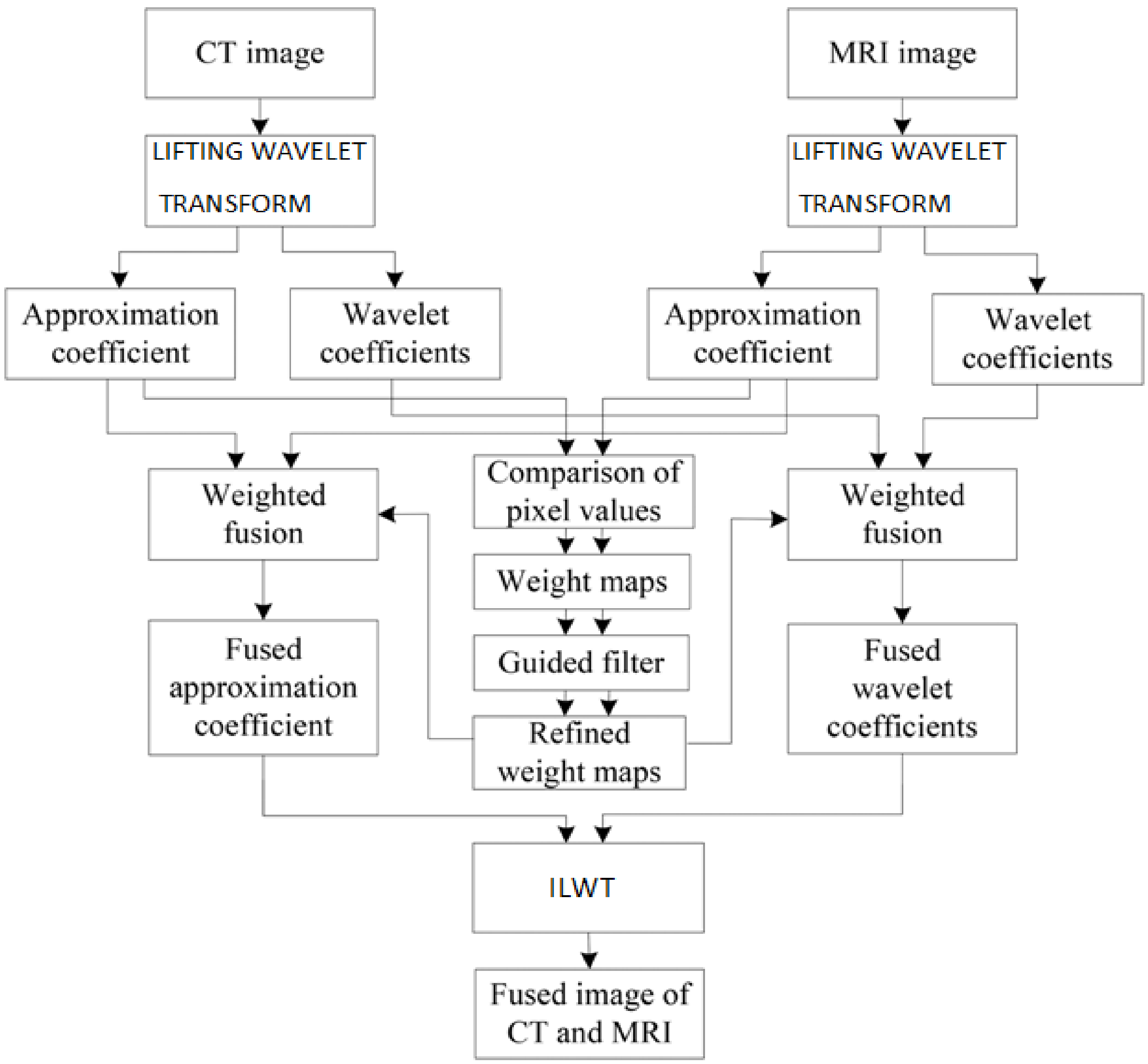


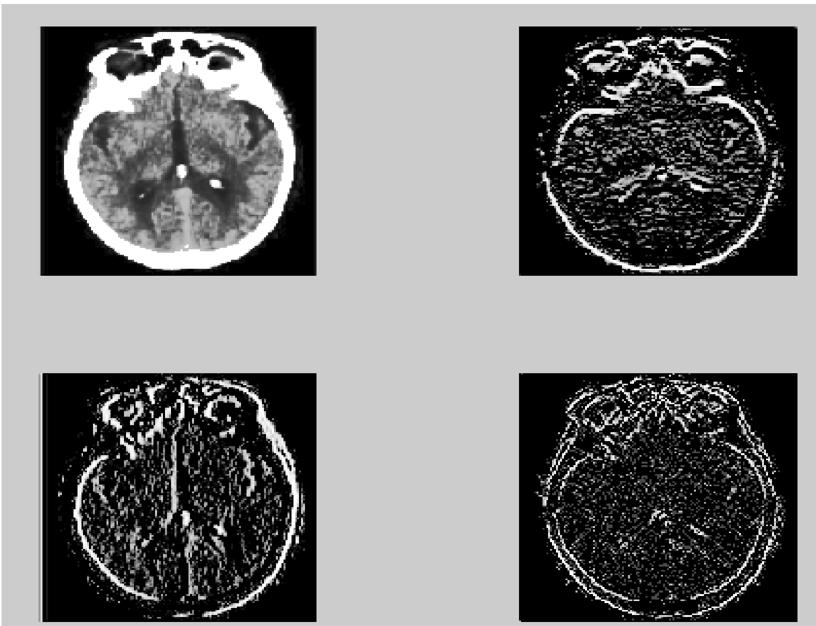
Fig.15 Flow chart of proposed method

In the proposed method the approximation coefficient and three wavelet coefficients of CT and MRI Images are determined by the application of Lifting wavelet transformation, respectively. The steps for this proposed algorithm are as follows:-

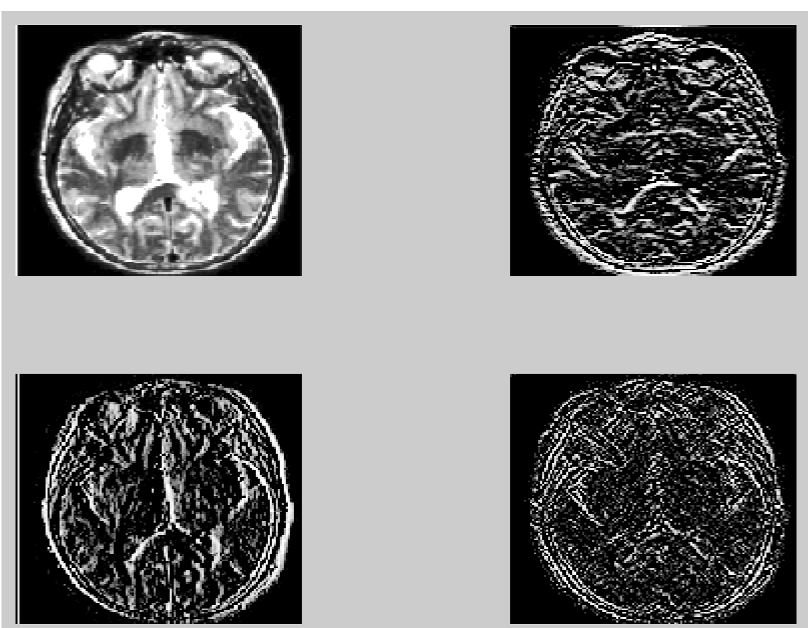
<u>STEP1</u>:- CT AND MRI BASED LIFTING WAVELET DECOMPOSI - TION :-

The LWT described in section 3 has been implemented on CT and MRI images to obtain the 4 subimages.

LWT subimages of CT by implementing LWT (Db4)



LWT subimages of MRI by implementing LWT (Db4)

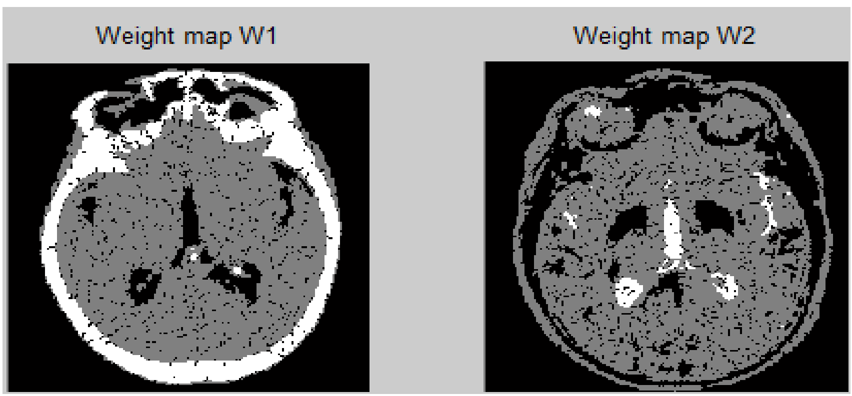


STEP2:- GENERATING WEIGHT MAPS

Initially after registration, Lifting wavelet transformation[7] have been implemented to CT and MRI images. TheA_1, H_1, V_1, D_1 are the LL, LH, HL and HH subimages of CT images and A_2,H_2, V_2, D_2 are the LL, LH, HL and HH subimages of MRI images. We used:

$$W_1 = \begin{cases} 1 & if \quad A_1 < A_2 \\ 0 & otherwise \end{cases}$$

$$W_2 = \begin{cases} 1 & if \ A_2 < A_1 \\ 0 & otherwise \end{cases}$$

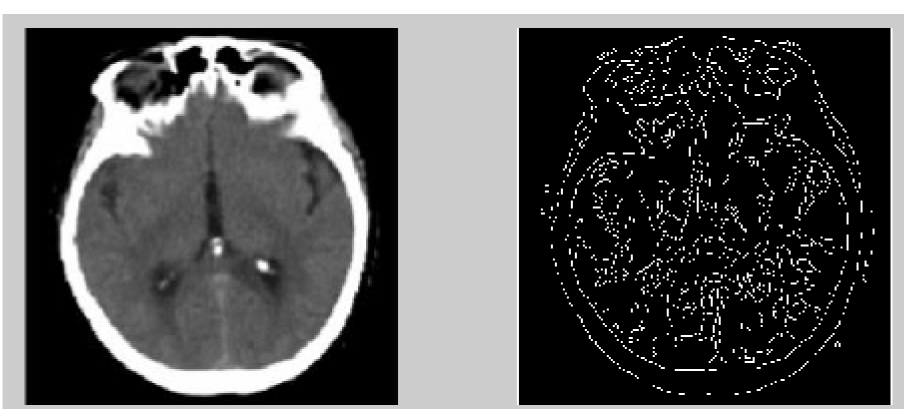


Refined weight maps

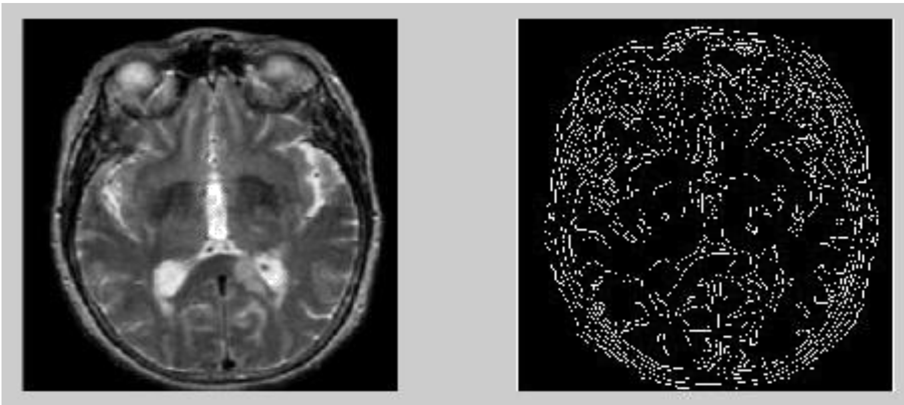
STEP3:-GUIDED IMAGE

Edges of CT and MRI images have been obtained by Canny edge detector and used as guided image for fusion purpose.

Canny detector output for CT image



Canny detector output for MRI image



<u>STEP4</u>:-GUIDED IMAGE FILTERING

Canny edge detected output are treated as guided image I(CT-MRI),while weight maps obtained after pixel comparison of wavelet transform are input image P of CT-MRI

Input :- filtering input image p, guidance image I, radius r, regularization $\in$

Output :- filtering output q

2.The edge detected output images is treated as the guided image I .

3 The weight map images is treated as the input image P .

4.A window w is used to obtain mean and variance of radius r

r = floor(win_size/2)

5. Now the coefficients a and b are computed as:-

$$a_k = \frac{1/|w| \sum_{i \in w_k} I_i P_i - \mu_k \bar{P}_k}{\sigma^2 - \in}$$

$$b_k = \bar{P}_k - a_k \mu_k$$

6.The a and b have been calculated using the method described in section 2.

7.Aoutput filtered image O which is derived using guided image I. The output is :-

$O_i = \frac{1}{|w|} (\sum_{k|i \in w_k} (a_k I_i + b_k)$

using$\sum_{k|i \in w_k} a_k = \sum_{k \in w_i} a_k$and due to the box symmetry of the window we have

$\overline{q_i} = \bar{a}_k I_i + \overline{b_k}$

where $\bar{a}_i = \frac{1}{|w|}(\sum_{k\in w_i} a_k)$ and $\bar{b}_i = \frac{1}{|w|}(\sum_{k\in w_i} b_k)$ are the average coefficients obtained by averaging all windows overlapping at pixel i. The averaging of overlapping windows is done for image denoising by using for guided filtering based algorithm.

STEP5:- USING ILWTTO OBTAIN FUSED IMAGE

A Guided Filter is designed using guided the approximation coefficient $A1$,$A2$ &weight maps $W1$ and $W2$ are used as the input images, respectively. Thereafter, the GF smoothens the weight maps. The optimum values of r and ε are derived by maximizing the cost function , while the various part of images have different r and ε values. Then,M_1 and $M_2$the refined weight maps are derived as shown below:-

$M_1 = G_{r,e}(W_1,A_1)$;

$M_2 = G_{r,e}(W_2,A_2)$;

Fusion of A_1 and A_2 provides approximation or LL coefficients of fused image and the LH , HL and HH subimages are fused according to the following expressions:-

A $= A_1 \times M_1 + A_2 \times M_2$

H $= H_1 \times M_1 + H_2 \times M_2$

V $= V_1 \times M_1 + V_2 \times M_2$

D $= D_1 \times M_1 + D_2 \times M_2$

Finally, the inverse lifting wavelet transform has been implemented on fused approximation and wavelet coefficients A, H, V,D respectively to obtain the fused image.

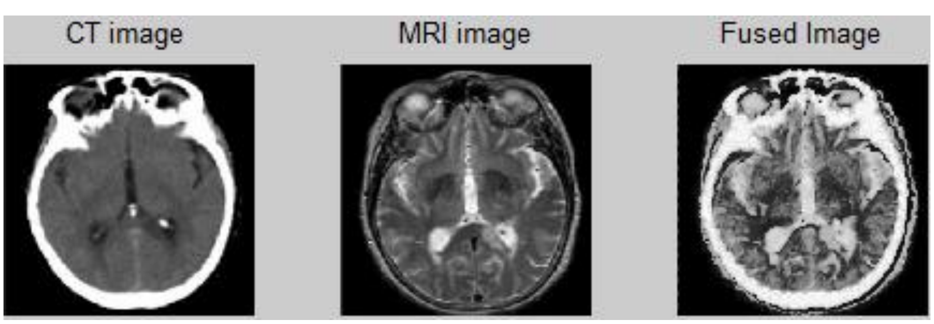


Figure22finalresults

STEP6.:-IMAGE FUSION EVALUATION

Analysis from GF shows the variation of r is from 1(minimum) to the maximum value(min (width − 1, height − 1))/2, where the number of pixels in the x direction of guided image is termed as width ,while the number of pixels in the y direction of guided image is termed as height, and min reflects the minimum operations. Use the following method to obtain the minimum value of r:-

Step1:- calculate evaluation parameters as $\bar{B}(1)$, $\bar{G}(1)$, $\overline{ES}(1)$ when r =1.

Step2:- Evaluation of a comprehensive parameters for various values of r are calculated as :-

Comprehensive evaluation parameter:- $\bar{C}(r) = \bar{B}(r)/\bar{B}(1) + \bar{G}(r)/\bar{G}(1) + \overline{ES}(r)/\overline{ES}(1)$

Step3:- The optimum r is obtained for maximum value of Comprehensive evaluation parameter $\bar{C}(r)$.

7.SIMULATION RESULTS

The method is implemented in MATLAB software on the MRI AND CT images of human brain following results are obtained in the form of fused image :-

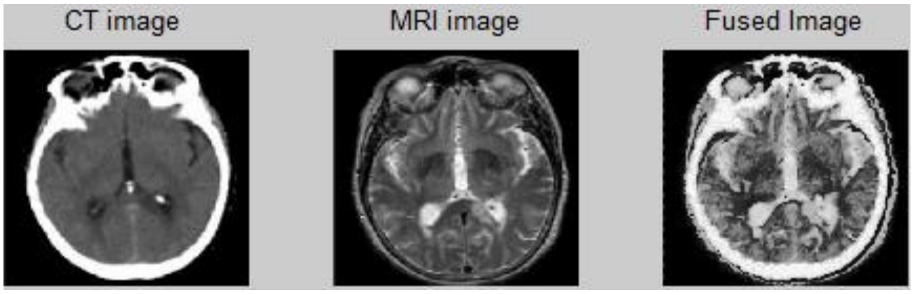


Fig.22 Final Fusion of CT-MRI

Fig.23 shows the variation of parameters with window size of radius r

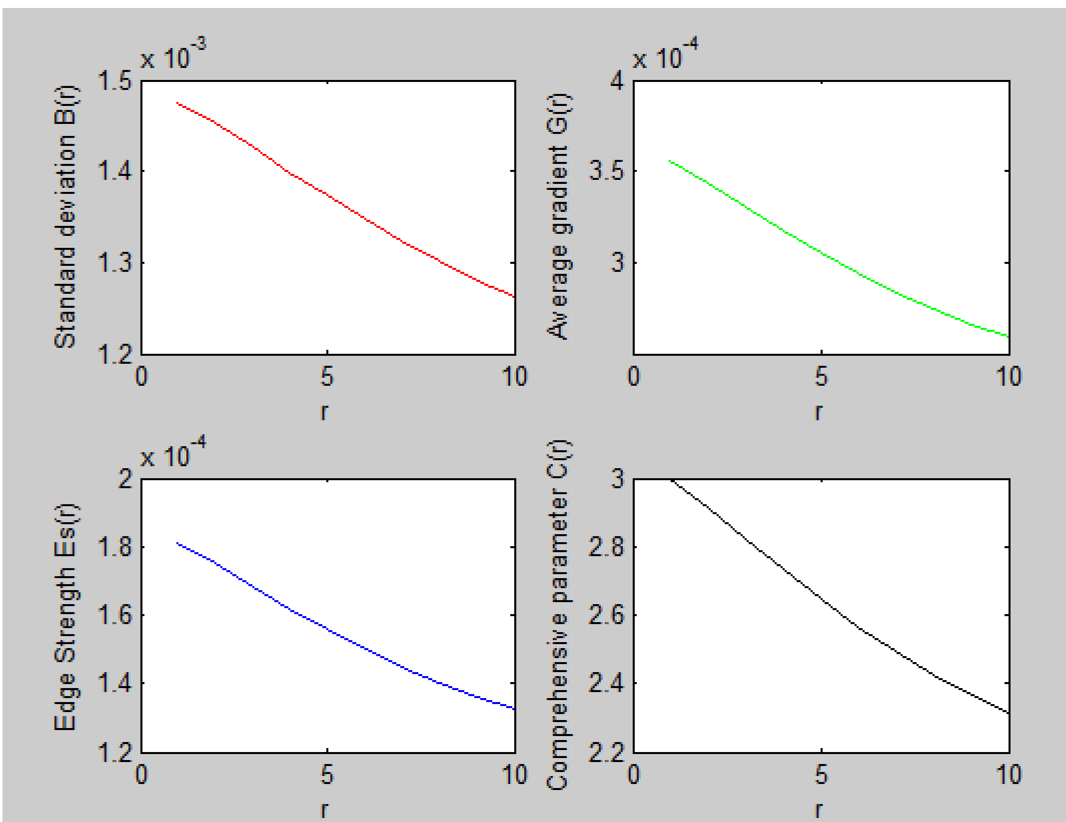


Fig.23 Parameter variation

<u>The results are</u>:-

Boundary parameters:-

Where G, ES, B are the average gradient, edge strength, and standard deviation

Optimum parameters for r_{opt} = 1 (floor(win_size/2));

$G_1 = 0.0964$	$ES_1 = 0.0483$	$B_1 = 0.3770$

Comparison of avg. parameters $G_{avg.}$,$ES_{avg.}$, $B_{avg.}$ of output fused image with original input

Parameters	**CT Image**	**MRI Image**	**Fused Image**
$B_{avg.}$	0.3138	0.2464	0.3766
$ES_{avg.}$	0.0359	0.0423	0.0490
$G_{avg.}$	0.0716	0.0845	0.0979

Comprehensive output parameter of the fused image

C = B/B_1 + G/G_1 + ES/ES_1 = 3.7299 **;**

Texture parameters:-Entropy and correlation

	CT Image	**MRI Image**	**Fused Image**
Entropy(H)	0.1978	0.1382	0.2714
Correlation(Rxx)	30.2735	50.2095	58.3674

According to the implementations done on the MATLAB the various performance parameters such as standard deviation , average gradient & edge strength of proposed algorithm are 0.396315, 0.565875 and 0.129778,respectively. The *r* = 8 gives the maximum values for the parameters, hence these three evaluation parameters which are earlier calculated by three methods for fusion are obviously lesser than those calculated by the proposed method for fusions. These results indicates that the fused image obtained after the fusion using proposed method contains largest accurate information against CT and MRI.

GROUP ALGORITHM	**STANDARD DEVIATION (Bavg.)**	**AVERAGE GRADIENT(Gavg)**	**EDGE STRENGTH(ESavg)**
GUIDED FILTER-DWT	0.3762	0.0978	0.0489
CHOOSE-m	0.3344	0.0484	0.0335
Fuzzy	0.3392	0.0551	0.0234
PROPOSSED	0.3766	0.0979	0.0490

8.CONCLUSION AND FUTURE WORK

8.1CONCLUSION

The design of guided filter is an important task for fusion purpose. In this work the guided filter is designed using weight map as guided image and the edge detected image by Canny edge detector as guided image. In this way the weight map of each image has been obtained from characteristics of the input images. Simulation results present the better results of the lifting based fusion methods as compared to other three methods.

8.2FUTURE SCOPE

We can use different denoising algorithms as preprocessing of medical images .Further improvement can be proposed using multi level decomposition.

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